



## Optimization under uncertainty of site-specific turbine configurations

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# Optimization Under Uncertainty of Site-Specific Turbine Configurations

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**Abstract.** Uncertainty affects many aspects of wind energy plant performance and cost. In this study, we explore opportunities for site-specific turbine configuration optimization that accounts for uncertainty in the wind resource. As a demonstration, a simple empirical model for wind plant cost of energy is used in an optimization under uncertainty to examine how different risk appetites affect the optimal selection of a turbine configuration for sites of different wind resource profiles. If there is unusually high uncertainty in the site wind resource, the optimal turbine configuration diverges from the deterministic case and a generally more conservative design is obtained with increasing risk aversion on the part of the designer.

## 1. Introduction

A commonly used phrase in the wind industry is “LCOE is king.” LCOE, the levelized cost of energy, is a standard metric to assess overall wind plant performance and cost and includes: energy production, all capital and operational expenditures, and effects from financing. Wind plant developers design to minimize LCOE through turbine selection, turbine placement, and infrastructure design. Ideally, all information relevant to the plant design would be known *a priori* so the LCOE could be optimized deterministically. Even assuming this perfect information, wind plant design optimization is a difficult problem to solve. A significant body of research has investigated deterministic wind plant optimization [1, 2]. In these cases, the problem was already difficult due to the nonlinearities and nonconvexities of the objective function and constraints. Earlier work focused on the problem of maximizing energy production from turbine placement subject to various constraints on interturbine spacing, excluded areas, and so on [1]. Recently, research studies have looked at the more global LCOE problem [1], and commercial wind plant design tools are increasingly incorporating methods to assess and optimize LCOE via the inclusion of turbine and infrastructure costs [2]. Whereas these LCOE optimization techniques have proved themselves useful in practical wind plant design, they are already computationally cumbersome. Practical tools often employ gradient-free optimization techniques [2] where optimization may take thousands of iterations, in which each iteration is costly so that it may take days to find an acceptable solution using a desktop computer. Parallelization and multistart approaches can be used to reduce the computational burden, but the complexity of the problem means that, under the best of conditions, finding a solution is computationally intensive.



Uncertainty affects all aspects of LCOE, whether issues that affect capital costs, turbine availability during procurement, component reliability through the plant lifetime, or variability in the wind resource over the plant's lifetime. Figure 1 shows factors that affect overall plant financial and LCOE uncertainty. The long-term uncertainty in the wind resource has a significant impact on LCOE. Including even this aspect of the overall uncertainty in the wind plant design problem becomes challenging from an optimization perspective.

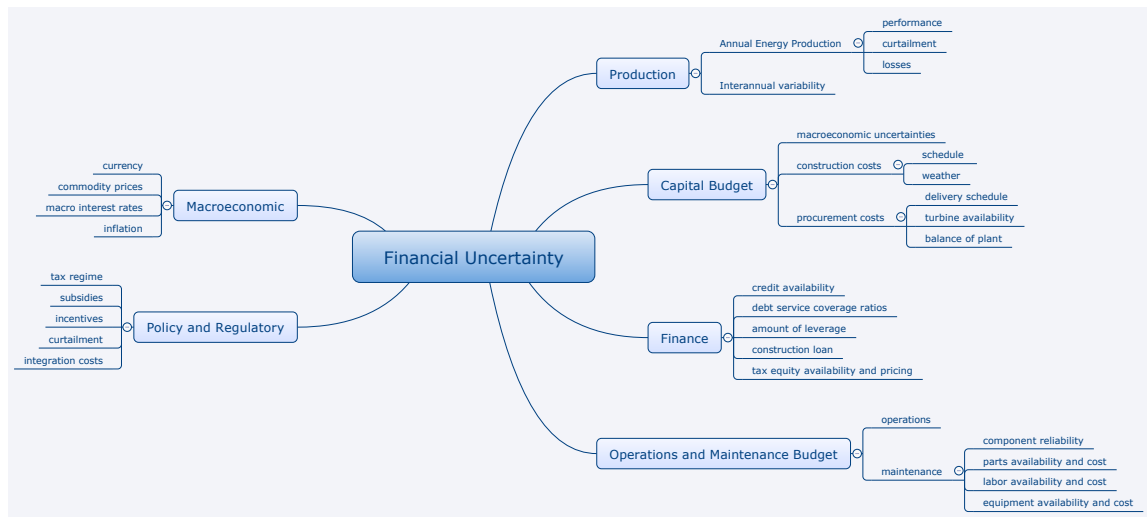


Figure 1: The U.S. Department of Energy Atmosphere to Electrons initiative has the mission of quantifying performance risk uncertainty and financing to identify and mitigate against various sources of uncertainty affecting wind plant financial viability. Illustration by Jason Fields, National Renewable Energy Laboratory

In this study, we examine an approach to incorporate wind resource uncertainty into the plant design process via a formal optimization under uncertainty (OUU) approach applied to a simple wind plant LCOE model. We take the perspective of a wind plant designer in the early stages of the development process who is trying to select a turbine for the plant to provide the best LCOE possible. In this case, the designer would take the limited resource information available, analyze it statistically to produce long-term trends, and then assess LCOE using simple models to represent plant energy production and costs for different turbine product offerings. To simplify the problem, we assume a large number of potential turbines with varying rotor diameters, rated powers, and hub heights, so we can turn the selection from a discrete to a continuous optimization. This could be viewed as the designer wanting to select the optimum turbine configuration for the site. As a second step, the designer would select the turbine which most closely matches the optimum configuration. With the simple cost model, this is now a straightforward optimization. The novel step is to allow the designer to incorporate an explicit representation of the uncertainty in the wind resource (in terms of wind speed and shear exponent) and to optimize for the turbine configuration that minimizes expected (and not deterministic) LCOE. In addition, with the OUU framework in place, the designer can now start to ask more sophisticated questions such as, “How do I minimize the 90<sup>th</sup>-percentile LCOE?” or, “How do I minimize the project risk of going over a specific LCOE threshold?” In so doing, the study shows that OUU techniques can be powerful tools to address the inherent uncertainty and associated risks during wind plant development.

## 2. Methodology

The intent of this study was to use a simple wind plant LCOE model in an OUU framework. The uncertainty considered was that in the model's wind resource inputs. This was done with generic distributions of these parameters to understand general trends as well as for real wind resource data for select locations in the United States. The latter distributions were developed using a measure-correlate-predict (MCP) process.

### 2.1. LCOE model

A simple wind plant cost and scaling model (CSM) was developed by the National Renewable Energy Laboratory (NREL) as part of the Wind Partnership for Advanced Component Technology [3]. Detailed design studies were performed and these results were abstracted into a simple parametric model of wind plant LCOE driven by key turbine and plant characteristics. Figure 2 shows the key input parameters and key outputs of the NREL CSM. This model has since been incorporated into NREL's Wind Plant Integrated Systems Design and Engineering Model (WISDEM<sup>TM</sup>) [4]. The WISDEM model includes a number of turbine and plant modeling tools built into an underlying, flexible, multidisciplinary wind plant modeling framework (the Framework for Unified Systems Engineering and Design of Wind Plants [FUSED-Wind]), developed in collaboration between NREL and DTU Wind Energy [5].

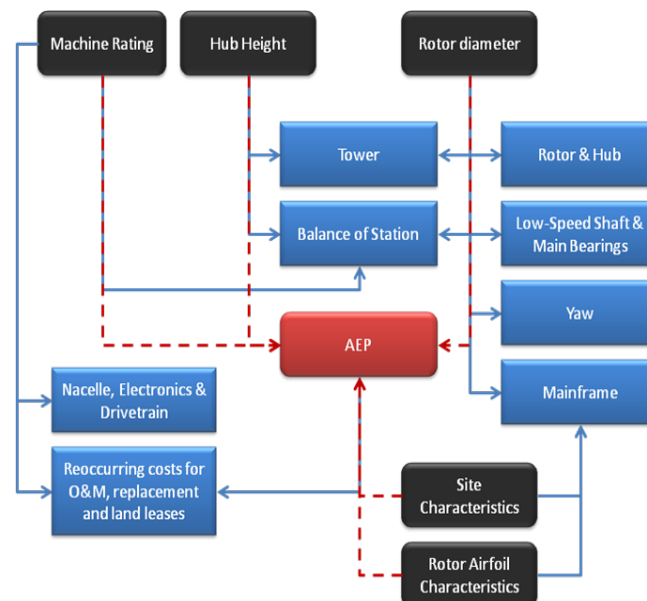


Figure 2: Logical flow of NREL CSM. Key inputs include the turbine configuration (rotor diameter, rated power, and hub height) and plant characteristics (wind resource, financing, etc.); key outputs include overall wind plant LCOE and its components.

In this model, the key configuration parameters of the turbine and overall plant characteristics are used to determine LCOE. Whereas the model has several limitations, in terms of outdated technology and costs, it is useful for this demonstration study because it calculates full wind plant LCOE based on a limited number of inputs. Thus, the model can be used to demonstrate broad trends in wind turbine configuration optimization under wind resource uncertainty. Future work will incorporate newer as well as higher-fidelity models that more accurately represent current technology and costs. A precursor to the OUU work involved a sensitivity analysis of the NREL CSM to uncertainty in the site wind resource parameters.

## 2.2. Optimization under uncertainty

This study examines the impact of using the annual variation in a site's measured wind resource to perform risk-averse optimization. Rated power, rotor diameter, and hub height of a wind farm with uniform turbine characteristics were optimized with respect to LCOE using traditional and risk-averse approaches. This study's risk-averse design via OUU differed from conventional optimization in that it ran several probabilistic simulations for each new set of design parameters, then created an aggregate of responses as the optimization objective (Figure 3). This allowed the measured deviation in the input to directly affect the optimization space.

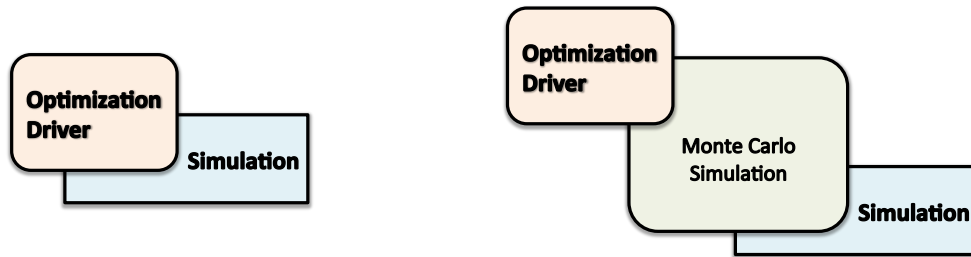


Figure 3: Traditionally, optimization consists of a driver sending parameters to an objective function (left). In this study, a stochastic simulation was run several times and an aggregate of the responses was used as the optimization objective (right).

Throughout this study, we compare the results of deterministic optimization to OUU. The deterministic optimization is simply to minimize LCOE with respect to rotor diameter, rated power, and hub height with the Weibull scale factor and shear coefficient fixed at their mean values. Two OUU objectives were examined: the expected LCOE (1) and the 90<sup>th</sup>-percentile LCOE (2). The two objectives were used to represent varying degrees of conservatism or risk aversion on the part of the designer.

$$\min \pi_s = E(LCOE(s, X)) \quad (1)$$

$$\min \pi_s = \pi_{90} \text{ s.t. } P(LCOE(s, X) \leq \pi_{90}) = 0.9 \quad (2)$$

where  $LCOE$  is the levelized cost of energy,  $s$  is the vector of design variables (rated power, hub height, and rotor diameter),  $X$  is a probability function describing normally distributed annual mean wind speed and shear exponent,  $E$  is the expected value function,  $P$  is the probability function, and  $\pi$  is the optimization objective to be minimized.

To perform the study, the WISDEM implementation of the NREL CSM was coupled to an uncertainty analysis method nested in an optimization routine. WISDEM and FUSED-Wind use an underlying software environment known as OpenMDAO for multidisciplinary design analysis and optimization. OpenMDAO has several built-in optimizers and analysis tools. Sandia National Laboratories' DAKOTA toolkit [6] provides a large number of parallelizable analysis tools—in particular for uncertainty analysis and quantification. As a precursor to this study, OpenMDAO was coupled with DAKOTA.

Risk-averse design case studies were performed for three U.S. sites. The sites' Weibull scale factor and shear exponent were quantified on an annual basis, then fitted to normal distributions. OUU was performed to find the optimal turbine rated power, rotor diameter, and hub height for each site, using the expected value and 90<sup>th</sup>-percentile of LCOE as optimization objectives. A gradient-free optimization approach was selected because the noise introduced by including

deviation in the input wind resource parameters was surprisingly large (as shown in Appendix A). A tournament-style, nonsorting genetic algorithm was run until convergence for each class-objective permutation. The algorithm used a population of 100, taking 14,000 Monte Carlo evaluations of the NREL CSM to form the optimization objective functions.

Three sites were identified as being appropriate for 80-m tall turbines of IEC 61400 classes one, two, and three [7], respectively. Multiheight high-resolution data were made available for each site through NREL's Plains Organization for Wind Energy Resources (POWER) project [8]. These wind speed data spanned approximately two years each. MCP analysis was used to relate the site wind speeds to reference data from the National Oceanic and Atmospheric Administration [9]. The "xgboost" extreme gradient boosting Python machine-learning package was used to conduct the MCP analyses. For each site, the MCP was used to create a 10-year data set. These data were used to generate probability density functions of the sites' annual mean Weibull scale factors and shear exponents by fitting distributions to the annual averages for the 10-year data set. Figure 4 shows the distribution of annual shear exponent and Weibull scale factor for the class-one site. Appendix B provides the distributions for the complete set of sites.

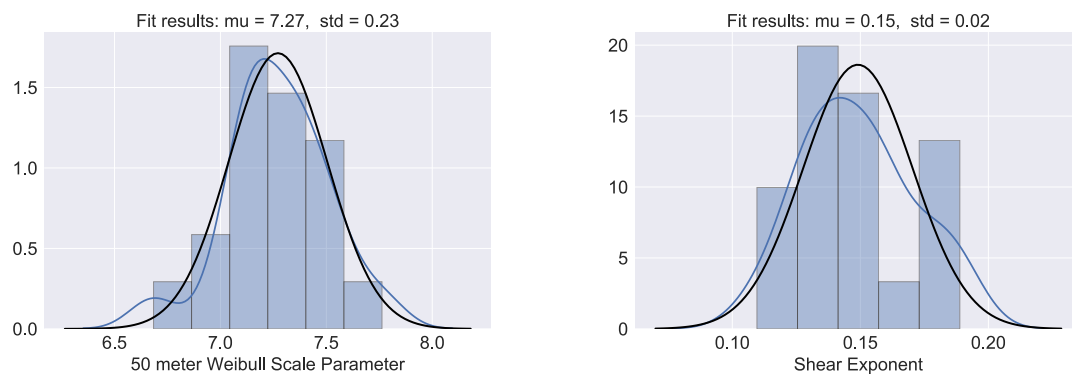


Figure 4: Empirical distribution and normal fit of annual mean Weibull scale factor (left) and shear exponent (right) in the IEC 61400 class-one site.

Finally, the sensitivity of the uncertain optimization formulations to deviation in NREL CSM wind resource inputs was investigated to demonstrate the level of variance in measured inputs required for the OUU approach to become significant.

### 3. Results

In the following sections, OUU turbine design results for theoretical and U.S. case studies are compared to the deterministic optimization results. Introducing wind resource uncertainty was observed to fundamentally change the design space of the NREL CSM, but only when the uncertainty was extreme. The deterministic optimization approach was observed to produce the same solutions as the uncertain design approaches for the U.S. cases. The optimal turbine design diverged from the deterministic solution when uncertainties larger than those observed in the U.S. sites were introduced.

#### 3.1. NREL CSM sensitivity analysis

To gain intuition regarding what to expect when we perform OUU, we first analyzed the sensitivity of NREL CSM's forecasted LCOE with respect to the site Weibull scale factor and shear coefficient (Figure 5). The setup for the analysis assumed a land-based wind plant using the WindPACT 1.5-MW reference design, which has a 61.5-m rotor diameter and 90-m hub



height. The Weibull scale factor is set in the NREL CSM via the 50-m height mean wind speed. All references to the Weibull scale parameter from this point forward imply association with 50-m height. As seen in Figure 5, the NREL CSM LCOE's sensitivity to the shear exponent and Weibull scale factor is convex (the sensitivity to shear exponent is slightly convex). The theorem of probability known as Jensen's inequality states that, for a convex function, the expected value of the function evaluated across a random variable will be greater or equal to the function evaluated at the distribution's expected value. Therefore, the convexity of LCOE with respect to the wind resource parameters implies that the expected LCOE across the Weibull scale factor and shear exponent probability distributions may be different than the LCOE evaluated at the expectation of the Weibull scale factor and shear exponent. In principle, this suggests that the deterministic and uncertain optimizations may differ.

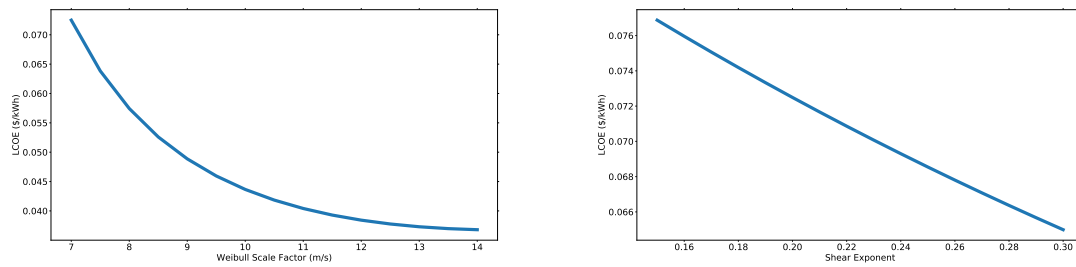


Figure 5: Sensitivity of LCOE with respect to (left) the 50-m mean wind speed (representative of the Weibull scale factor) and (right) site shear exponent.

Furthermore, a set of equations can be derived explaining this nonlinearity. The wind speed for a given height can be calculated from a known scale factor and shear exponent:

$$U = \frac{1}{2} \sqrt{\pi} \lambda \left( \frac{z}{z_{50}} \right)^k \quad (3)$$

where  $U$  is mean wind speed at the hub height (m/s),  $z_{50}$  is 50 m,  $z$  is the hub height (m),  $k$  is the shear exponent, and  $\lambda$  is the Weibull scale factor (m/s).

This relationship can change by integrating across a probability distribution of a stochastic parameter. If the Weibull scale factor and shear exponent are normally distributed, as in our OUU cases, the hub-height wind speed can be found for a given distribution for the scale factor, shear exponent, or both:

$$U|\mathbf{K} = \frac{1}{2} \sqrt{\pi} \lambda \left( \frac{z}{z_{50}} \right)^{\mu_K} e^{\frac{1}{2} \sigma_K^2 \log \left( \frac{z}{z_{50}} \right)^2} \quad (4)$$

$$U|\boldsymbol{\lambda} = \frac{1}{2} \sqrt{\pi} \mu_{\lambda} \left( \frac{z}{z_{50}} \right)^k \quad (5)$$

$$U|\boldsymbol{\lambda}, \mathbf{K} = \frac{1}{2} \sqrt{\pi} \lambda \left( \frac{z}{z_{50}} \right)^{\mu_K} e^{\frac{1}{2} \sigma_K^2 \log \left( \frac{z}{z_{50}} \right)^2} \quad (6)$$

where  $\mathbf{K}$  is a normally distributed shear exponent,  $\boldsymbol{\lambda}$  is a normally distributed Weibull scale factor (m/s),  $\sigma_X$  is the standard deviation of normally distributed variable  $X$ , and  $\mu_X$  is the mean value of normally distributed variable  $X$ .



These results demonstrate that the expected hub height wind speed scales with the deviation in measured shear exponents. The expected power can be described as a function of a normally distributed annual mean wind speed:

$$P|U = \int_{i=0}^{\infty} P(u)N(\mu_u, \sigma_u)du \quad (7)$$

where  $N(a, b)$  is a Gaussian probability distribution with mean  $a$  and standard deviation  $b$ , and  $P$  is power generated (MW).

This could be conceived of as a variable-speed turbine's power curve corrected for turbulence intensity, neglecting the rotor inertia. The effects of the different values of this "inertia-free TI" are shown for 68% and 95% confidence intervals (Figure 6). These relationships explain the nonlinearity of LCOE with respect to the site's Weibull scale factor and shear exponent.

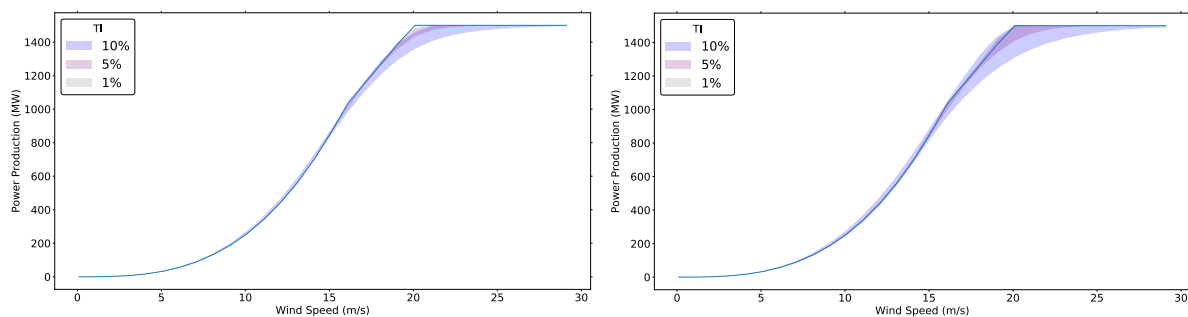


Figure 6: Generic power curve modified to reflect uncertainty in the annual Weibull scale factor, which can be formulated as TI power curve modifications neglecting inertia, for 68% and 95% confidence intervals (left and right, respectively).

The NREL CSM expected LCOE was examined with respect to the standard deviations of normally distributed, site-specific, Weibull scale factor and shear exponent. For this study, the same land-based plant was used with a wind shear exponent of 0.24 and a Weibull scale factor of 7.03 m/s. Figure 7 shows the sensitivity of expected cost of energy with respect to the standard deviation of the Weibull scale factor and shear exponent. Introducing deviation of these wind resource parameters increased the expected lifetime cost of energy because the expected annual energy production was reduced.

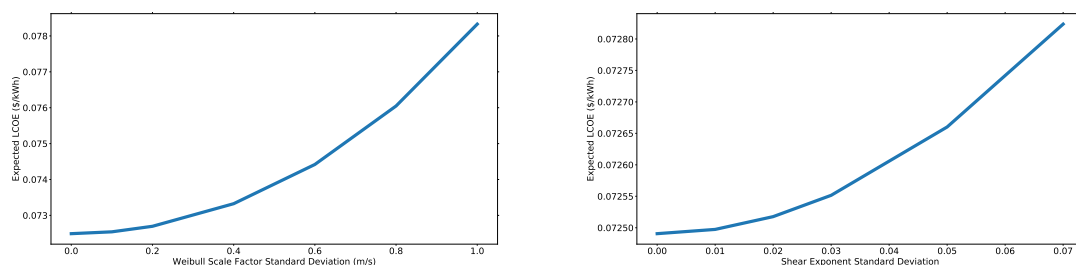


Figure 7: NREL CSM lifetime cost of energy as a function of the annual standard deviation of the site's Weibull scale factor (left) and shear exponent (right).

The sensitivity analysis demonstrated the nonlinearity of our objective function (in this case expected LCOE) as a result of uncertainty in the Weibull scale factor and shear exponent. The

modification of the power curve will only serve to compound this, because for each external iteration of the OUU analysis, a new power curve will be constructed and mix with the resource uncertainty to affect overall LCOE objectives. For these reasons we do expect to see some divergence between deterministic and uncertain optimization formulations.

### 3.2. U.S.-based cases

Next, a set of OUU studies for the U.S. wind sites was run using the expected value and 90<sup>th</sup>-percentile LCOE as optimization objectives. Three sites were selected with a range of uncertain wind speeds and shear exponents (Table 1). The solutions turned out to be the same in the uncertain and deterministic formulations of each case. This is because, for the observed uncertainty in the wind resource parameters, the design spaces of the deterministic and uncertain problem formulations are very similar. The optimal turbine characteristics associated with these results, for each U.S. case, is shown in Table 2.

Table 1: 50-m Weibull scale factor and shear exponent means and standard deviations for Gaussian distributions of the NREL CSM site wind resource inputs.

Site	1	2	3
Mean/Std dev 50-m Weibull scale factor	7.27 / 0.23	6.35 / 0.15	5.50 / 0.26
Mean/Std dev shear exponent	0.15 / 0.02	0.17 / 0.02	0.27 / 0.02

Table 2: Optimal turbine characteristics found for each site. They are the same for both the deterministic and uncertain formulations.

Site	1	2	3
Rotor Diameter (m)	109	123	140
Rated Power (MW)	2.21	2.37	3.04
Hub Height (m)	63	78	122

The results for both the deterministic and uncertain optimization show the expected trend of increasing hub height and decreasing specific power as we move to lower wind speed sites.

### 3.3. Optimal rotor diameter sensitivity to deviation in the annual mean Weibull scale parameter

Section 3.1 suggests it is possible for OUU and deterministic optimizations to disagree. However, in section 3.2 we found that, for realistic sites, no such disagreement was observed. In this section, we increased the standard deviation of the Weibull scale factor to identify what magnitude of uncertainty will make this disagreement evident. The sensitivity of the optimal rotor diameter was investigated with respect to uncertainty in the annual Weibull scale factor for three theoretical wind plant designs. The optimal rotor diameter was observed for different deviations in the mean annual Weibull scale parameter for each case, for which the associated parameters are shown in Table 3. These cases were selected to be representative of present (case 1), future (case 2), and past (case 3) wind farm technologies.

The optimal rotors associated with the expected and 90<sup>th</sup>-percentile LCOE objective formulations for test case one are shown in Table 4. For low uncertainties, as in Section 3.2, the deterministic and uncertain optimization formulation results are the same. When the standard deviation of the Weibull scale factor is increased, the deterministic and uncertain optimization formulation results diverge. Similarly, Tables 5 and 6 show solutions for the two uncertain

Table 3: Parameters used for three theoretical test cases.

	Case 1	Case 2	Case 3
Hub Height (ft)	100	140	60
Rated Power (MW)	2.3	3.5	0.80
Mean Annual Wind Speed (m/s)	9	10	7
Shear Coefficient	0.15	0.2	0.15

optimization formulations associated with test cases two and three, respectively. Figure 8 shows the rotor diameter design space of the expected value and 90<sup>th</sup>-percentile objectives for case one, and is representative of the trend observed in cases two and three. In all cases we do in fact see that, for large enough uncertainties, the deterministic and uncertain optimization formulation results differ.

Table 4: Optimal rotor diameters associated with the expected value and 90<sup>th</sup>-percentile objective functions for test case one (m). The deterministic solution is 96 m, independent of Weibull scale factor deviation. dev(WS) symbolizes the standard deviation of the Weibull scale factor.

	dev(WS)=0.2m/s	dev(WS)=0.5m/s	dev(WS)=1m/s	dev(WS)=2m/s
Expected Value	96	96	99	104
90 <sup>th</sup> -Percentile	96	103	107	123

Table 5: Optimal rotor diameters associated with the expected value and 90<sup>th</sup>-percentile objective functions for test case two (m). The deterministic solution is 110 m, independent of Weibull scale factor deviation.

	dev(WS)=0.2m/s	dev(WS)=0.5m/s	dev(WS)=1m/s	dev(WS)=2m/s
Expected Value	110	110	111	118
90 <sup>th</sup> -Percentile	110	114	119	133

Table 6: Optimal rotor diameters associated with the expected value and 90<sup>th</sup>-percentile objective functions for test case three (m). The deterministic solution is 78 m independent of Weibull scale factor deviation.

	dev(WS)=0.2m/s	dev(WS)=0.5m/s	dev(WS)=1m/s	dev(WS)=2m/s
Expected Value	78	78	81	90
90 <sup>th</sup> -Percentile	78	82	90	105

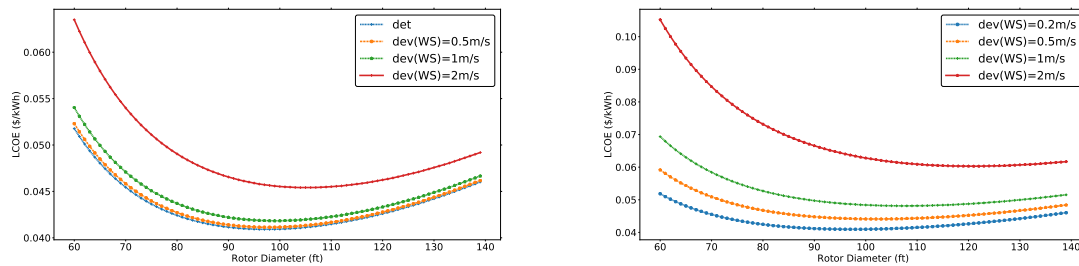


Figure 8: Sensitivity of rotor diameter design space with respect to Weibull scale factor annual deviation for expected value (left) and 90<sup>th</sup>-percentile (right) objectives.

#### 4. Discussion and conclusions

The explicit consideration of uncertainty offers a new approach to wind plant optimization. In this study, we demonstrated an OUU approach to turbine configuration optimization under uncertainty for different risk profiles. Through our sensitivity analysis, it was shown that increasing variance in the inputs caused an increase in the expected LCOE. This led to OUU results where greater conservatism was found for the uncertain optimizations relative to the deterministic case but only for highly uncertain cases. In particular, the optimal specific power of the turbine configuration tended to increase, moving from the deterministic to the expected LCOE to the 90<sup>th</sup>-percentile LCOE objective functions.

The optimal specific power for the turbine increased from the lower wind speed to the higher wind speed sites in both the deterministic and highly uncertain cases. Moving from the deterministic case, wherein the wind resource is described as an exact Weibull distribution, to one in which there is large uncertainty in the Weibull scale factor places downward pressure on the specific power at all wind speeds. In other words, in order to address the uncertainty of the wind resource, the designs for each wind speed became more conservative with a larger ratio of swept area to power produced.

The wind plant LCOE model used in this study was quite simple and intended only to be illustrative of the approach. In the future, more recently developed and higher-fidelity models will be used to investigate wind plant design under uncertainty. This study illustrated the potential for OUU approaches to improve the wind system design process from the perspective of more explicitly addressing stakeholder risk appetites.

#### 5. Acknowledgments

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## 6. References

- [1] J. Hebert-Acero, Probst O., P.E. Rethore, G. Larsen, and K. Castillo-Villar. A review of methodological approaches for the design and optimization of wind farms. *Energies*, 7(11):6930–7016, October 2014.
- [2] E. Yilmaz. Benchmarking of optimization modules for two wind farm design software tools. Master's thesis, Gotland University, 2012.
- [3] L. Fingersh, M. Hand, and A. Laxson. Wind turbine design cost and scaling model. Technical Report NREL/TP-500-40566, National Renewable Energy Laboratory, December 2006.
- [4] National Renewable Energy Laboratory. WISDEM. <https://github.com/WISDEM/WISDEM/>.
- [5] National Renewable Energy Laboratory and DTU Wind Energy. FUSED-Wind. <https://github.com/FUSED-Wind/fusedwind/>.
- [6] Sandia National Laboratories. DAKOTA. <https://dakota.sandia.gov>, 2015.
- [7] IEC. 61400-1. wind turbines—part 1: Design requirements, 2005.
- [8] Und/power database. internal database at the national renewable energy laboratory, originally funded by the u.s. department of energy. (multiheight high-resolution wind speed dataset for several u.s. sites [accessed february 20, 2016]).
- [9] NOAA/NCI find a station data tool. <https://www.ncdc.noaa.gov/cdo-web/datatools/findstation> (daily summaries data set; accessed [accessed february 20 through march 25, 2016]).

## Appendix A. Analysis of objective function noise

A gradient-free optimization approach was selected for this OUU because the noise introduced by including deviation in the input parameters was surprisingly large. The number of samples required for an objective function sufficiently smooth for gradient-based optimization was judged to dwarf the time advantage of gradient-based vs. gradient-free optimization. The ninetieth percentile objective was observed to take several orders of magnitude more samples than the expected value objective to achieve sufficient convergence (Figure A1).

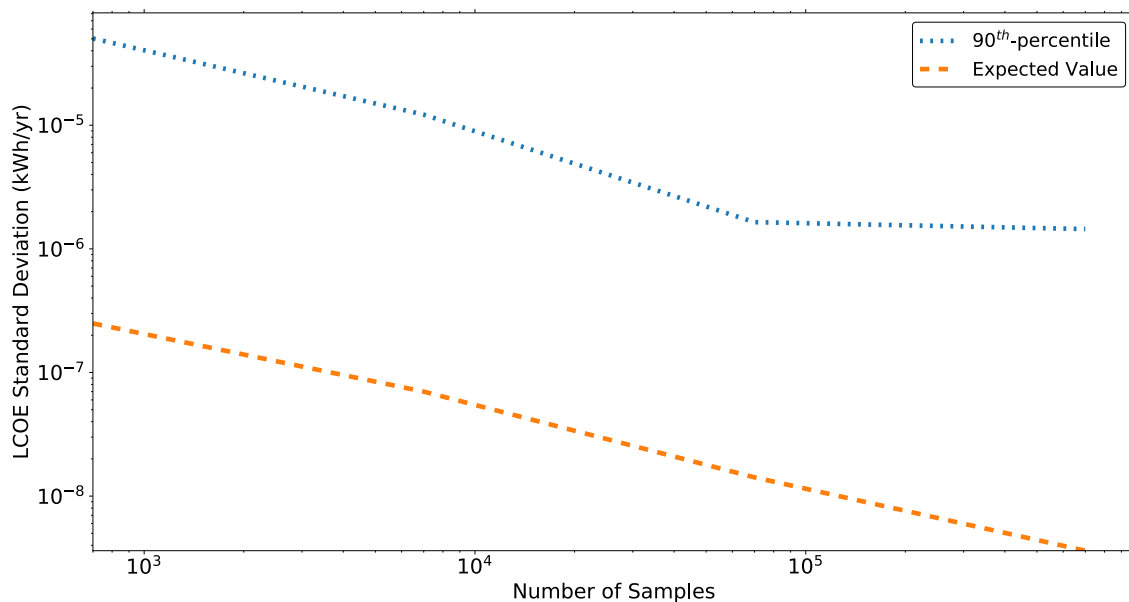


Figure A1: Average objective function standard deviations for expected value and 90<sup>th</sup>-percentile objectives as a function of Monte Carlo number of samples used.

## Appendix B. Wind Resource Distributions for U.S. Sites

The MCP analysis was used to generate normal fits to the annual shear exponent and Weibull scale factor distributions for each U.S. site (Figure B1).

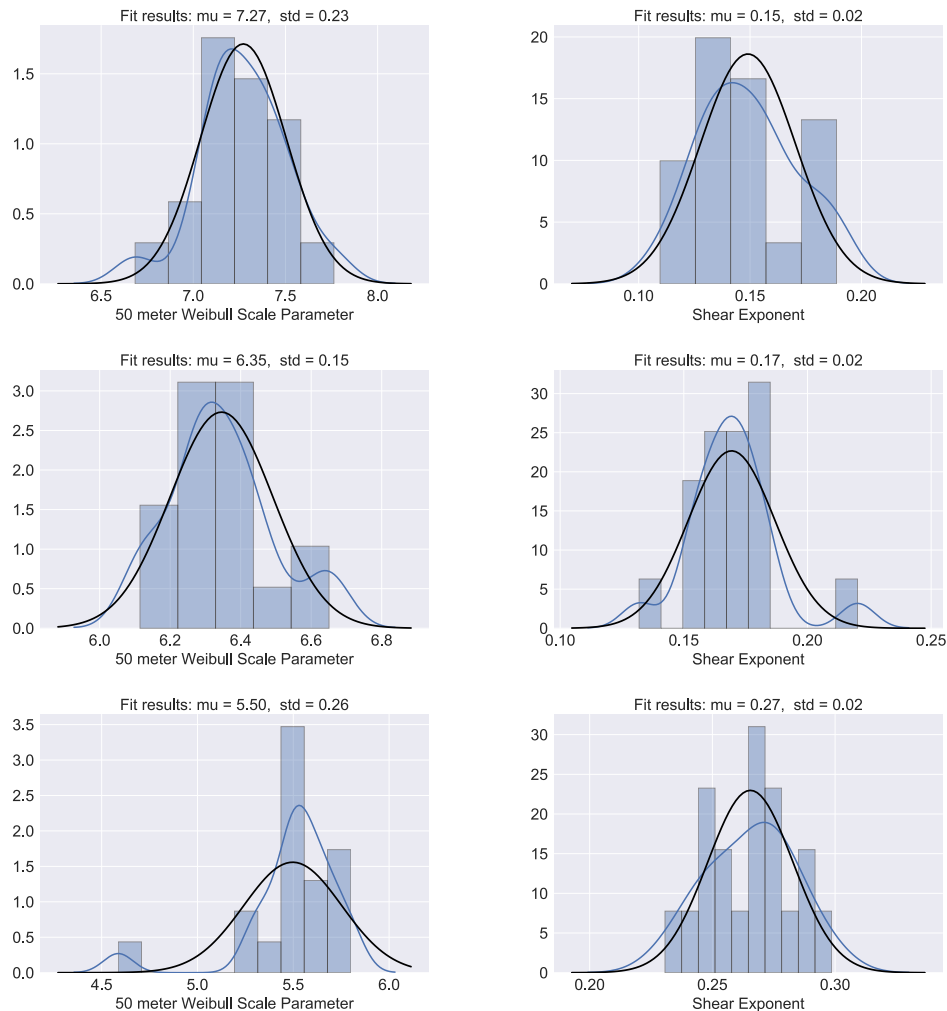


Figure B1: Empirical distribution and normal fit of Weibull scale coefficient (left) and shear exponent (right) in sites suitable for class one (top), class two (middle), and class three (bottom) turbines.